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ANALYSIS OF GROUNDWATER LEVEL FLUCTUATION IN A PLAIN AREA USING GENETIC ALGORITHMS AND AN ARTIFICIAL NEURAL NETWORK

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ABSTRACT: This paper reports on a research study that investigated a robust artificial neural network (ANN) and linear combination enhanced by genetic algorithms (LC-GA) technique for analyzing groundwater level (GL) in a plain area of the Saitama prefecture in Japan. The back propagion algorithm is used in ANN model. The input sets were selected by employing an analytical technique, the cross-correlation of monthly GL. The major objective of this study was to develop a reliable groundwater level fluctuation analysis system by means of GL prediction, which have different fluctuation patterns in a plain area generating trend forecasts for the forthcoming GL monitoring and management. In general, the LC-GA model gives better prediction in testing period than the ANN model even though it has out range from training data. It was found that by inserting one time lag gives better prediction results for ANN and LC-GA models.

Keywords: Groundwater level, artificial neural network, back propagation, genetic algorithms, linear combination, prediction

INTRODUCTION

Groundwater is the most important water resource for many countries. Groundwater is not only used for domestic and municipal consumption, but also for agricultural and industrial water supply. Groundwater management approaches based on a variety of simulation and prediction techniques and control measures have been proposed and adopted by researchers and relevant authorities to address the problem of providing long-term countermeasures against land subsidence and the protection of groundwater resources in the region.

Land subsidence can be considered to be one of the most prominent groundwater problems that cause serious damage, especially to infrastructure and the environment. The losses due to the irreversible phenomenon of subsidence are always found to be huge in social, financial and environmental terms. Because of the severity of the damage, maintaining groundwater level (GL) becomes a critical issue. In other words, groundwater resource development should be performed under controlled conditions.

The GL at any point is stochastically distributed. When the pumping rate at some points is increased, the relationship among them changes. The effect of increasing groundwater abstraction can be evaluated by investigating the observed value and estimated value from other observation wells. A stochastic model, such as artificial neural networks (ANN) can be used to approach the GL problem. ANN is robust methods applied in this research for analyzing groundwater level fluctuation. The hybrid linear combination (LC) and genetic algorithm (GA) and called LC-GA is proposed method in this study. The result of ANN and LC-GA is compared.

Several researchers have carried out the application of ANN to the groundwater problem. ASCE Task Committee (2000a, 2000b) presented concepts and the application of ANN in hydrology. Ranjithan et al. (1993) presented an ANN-based screening tool for identifying critical realizations from a large set of uncertainty in hydraulic conductivity parameter. ANN was developed and used to estimate aquifer parameter values (Balkhair, 2002). Maier and Dandy (2000) evaluated the ANN for the prediction and forecasting of water resource variables. ANNs have also been applied in groundwater management problems (Coppola Jr. et al., 2003). Lallahem et al. (2005) evaluated groundwater level in fractured media using a neural network. Coulibaly et al. (2001) simulated water table fluctuation using an ANN with hydrometeorological data as input. Daliakopoulos et al. (2005) evaluated several different neural networks' architecture for groundwater level forecasting.

In addition, the applications of GA for groundwater

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problems have increased recently. Prasad and Rastogi (2001) used GA coupled with a finite element method to estimate groundwater recharge. Giacobbo et al. (2002) investigated the feasibility of using genetic algorithms for estimating the parameters of groundwater contaminant transport. Katsifarakis et al. (1999) combined the boundary element method and GA to find optimal solutions to commonly encountered groundwater flow and mass transport problems. Morshed and Kaluarachchi (1998) compared ANN and GA in flow and transport simulation.

In the present study, backpropagation artificial neural networks (BPANN) and linear combination with genetic algorithms (LC-GA) are applied to analyze the groundwater level. The selection of data as input set was conducted by using cross-correlation between input candidates and desired output. The input set contains five of the GL from other observation wells which are the highest fifth of correlation coefficient with respect to the GL studied. The objective of this study was to develop a reliable groundwater level fluctuation analysis system by means of GL prediction to generate trend forecasts for the forthcoming monitoring and management period, based on observed data from the past eight years. For an overall development of the basin, a continuous forecast of the GL is required to effectively use any simulation model for water management (Nayak et al., 2006).

MATERIAL AND METHODS

Genetic Algorithms

Genetic algorithms (GA) are introduced by Goldberg (1989). The GA is stochastic search techniques based on the mechanism of natural selection and natural genetic (Gen & Cheng, 1997). The solution to a problem solved by genetic algorithms uses an evolutionary process. The inspiration for GA came from nature and survival of the fittest. In a population, each individual has a set of characteristics that determine how well suited it is to the environment. Survival of the fittest implies that the "fitter" individuals are more likely to survive and have a greater chance of passing their "good" features to the next generation. The algorithm begins with a set of solutions (represented by chromosomes) called the population. Solutions from one population are taken and used to form a new population. This is motivated by a hope that the new population will be better than the old one. Solutions, which are then selected to form new solutions (offspring), are selected according to their fitness. This is repeated until some condition (for example number of populations or improvement of the best solution) is satisfied.

In this study GA was used to optimize the weight or coefficient of the linear combination (see Eq. 1). The input set of LC-GA model used as same as ANN model selected by cross correlation of inputs and target of GL interest.

$$y = \alpha_1 * x_1 + \alpha_2 * x_2 + \alpha_3 * x_3 + \alpha_4 * x_4 + \alpha_5 * x_5 \quad (1)$$

where y is output model, and $x_1, \ldots, x_5$ is the variable input having the highest value of correlation coefficient with respect to the desired output. The $\alpha_1, \ldots, \alpha_5$ is a coefficient or weight of the linear combination.

Artificial Neural Networks

An artificial neural network is different from a conventional system such as an analytical or statistical model. An ANN is a network consisting of an arbitrary number of very simple elements called nodes. Each node is a simple processing element that responds to the weighted inputs it receives from other nodes (Lee et al., 2004). A common type of ANN consists of three layers: an input layer is connected to a hidden layer, which is connected to an output layer (Fig. 1).

The arrangement of the nodes is referred to as the network architecture. Various network architectures are available. One of them that are applied in much research is a multi-layer backpropagation neural network. The first operation is the feed forward operation. During this operation each node j receives incoming signals from every node i in the previous layer. Each incoming signal (y_i) associates with a weight (w_{ji}). The net input, x_j, to node j is a sum of all the incoming signal times the weight as described in Eq. (2).

$$x_j = \sum_i y_i w_{ji} \quad (2)$$

Note that this includes an extra node we call the bias node, which is assumed to have a value of 1 at all times. The weight on this extra node is called the bias as a threshold value.

The outgoing signal yj, which is a non-linear function, is produced by a transfer function of its input. The most commonly used transfer or activation function is the sigmoid function. The sigmoid function is, in essence, a smooth version of a step function. It is zero for low input. At some point it starts rising rapidly and then, at even higher levels of input, it saturates. The characteristic of a sigmoid function is differentiable everywhere. The logistic sigmoid function takes the form of:

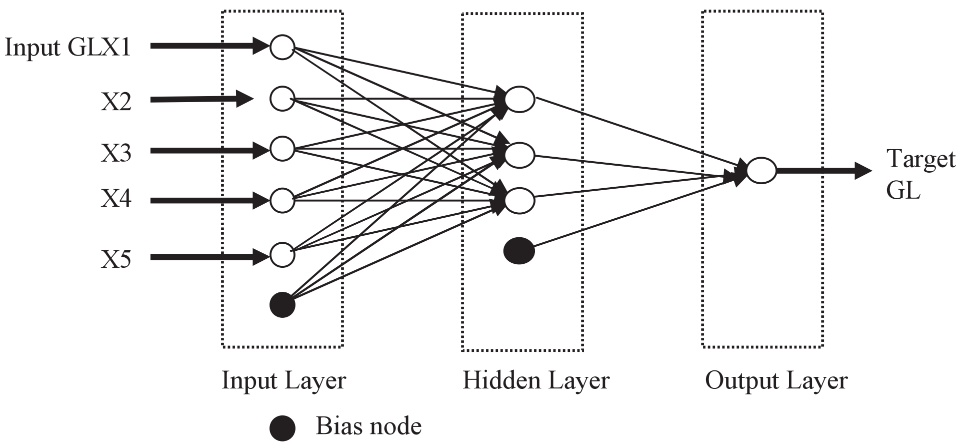

Fig.1 Topology of three-layer feed forward Artificial Neural Network

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

The nonlinear nature of this sigmoid transfer function plays an important role in the performance of the ANN. Other functions can be used as long as they are continuous and possess a derivative at all points.

The backward pass is concerned with error computation and weight update. The algorithm that is usually used in this operation is a backpropagation algorithm. Backpropagation artificial neural networks (BPANN) were introduced by Rumelhart et al. (1986), and a good description of the BPANN in groundwater problems can be found in Ranjithan et al. (1993) and ASCE Task Committee (2000a, 2000b), among others.

The backpropagation algorithm is a gradient descent procedure used to minimize an objective function (error function) E. When the calculated outputs are carried out, the next step is to calculate the difference or error between calculated outputs and desired (target) output. If the overall error value drops below some predetermined threshold, then the model is completed. If not, error backpropagation, one of the procedures to use adjusted weights, begins. This means that the error value is then propagated backwards through the network, and small changes are made to the weights in each layer. The sum-squared error value is given by:

$$E = 0.5 \sum_{k} \left(t_k - o_k \right) \tag{4}$$

The error, E, for one training sample is a function of the desired output, t, and actual output, o. The goal of the training process is to minimize this sum-squared error over all training patterns.

There are several variations of the backpropagation algorithms; the gradient descent with momentum is applied in this research. Without momentum a network may get stuck in a shallow local minimum. With momentum, a network can slide through such a minimum. This technique is one of the simplest and most widely used first-order parameter optimization procedures. The new vector W_{k+1} is adjusted according to:

$$W_{k+1} = W_k - \eta\, g_k + \alpha\, W_{k-1} \tag{5}$$

where W_k and g_k are weight and error gradient with respect to weight for k-th iteration. The learning rate (η) and momentum (α) are selected by trial and error procedure. The momentum term determines the proportion of the update step due to the current gradient versus the last update step. The training parameter was 0.5 for learning rate and 0.9 for momentum factor. The maximum iteration or epoch was 5000 with error goal of 1exp (-5).

STUDY AREA

The study area was Saitama prefecture, one of the local governments in Japan, the area of which is located in the middle of the Kanto district, north of Tokyo. The area of Saitama prefecture is 3,799km2, and the population is about 7 million. The lowland and upland occupy about 60% of the entire prefecture, but about 97% of the population is concentrated on the lowland and upland regions. Therefore, there are many activities in the area, including groundwater abstractions for many purposes. There are an estimated number of more than 7000 pumping wells distributed all over the Saitama Plain to extract groundwater for drinking, industrial and agricultural purposes, and about 67 observation wells for monitoring purpose. Some locations have more than one observation well such as Urawa, it has two wells (see Fig. 2). The 67 observation wells are in lowland and upland areas, with the deepest well at 700m and the shallowest

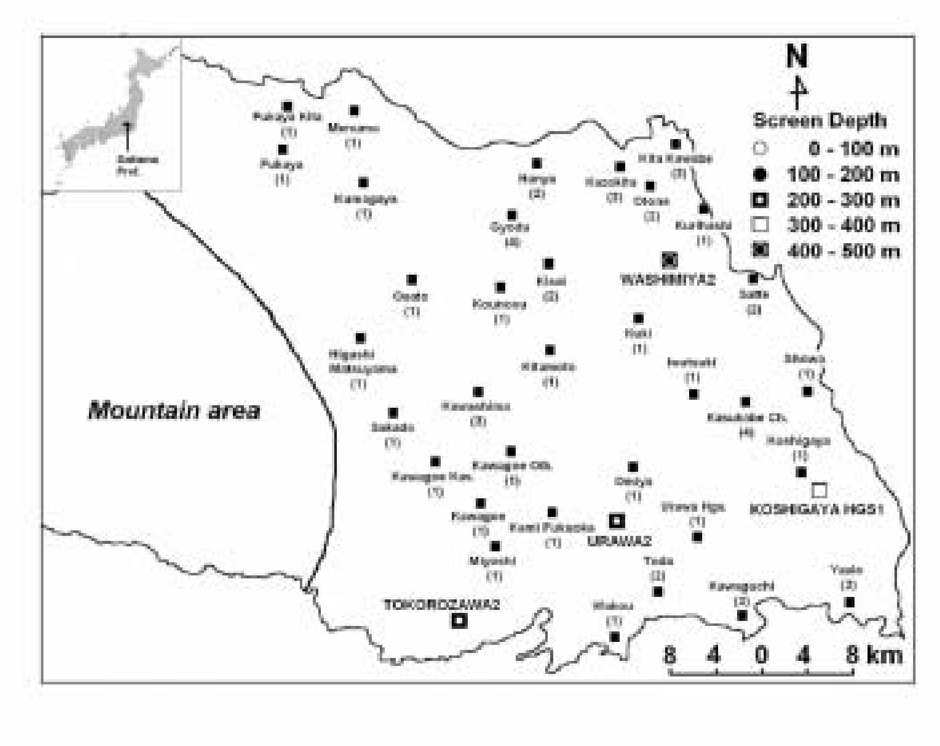

Fig. 2 Map of the observation wells in Saitama prefecture

at 35m below the land surface.

The study area has been divided into four groundwater control areas, each covering an approximately equal land area of similar hydrologic characteristics. The demarcations for these control areas are mostly the administrate boundaries of cities, towns and villages. The control areas are located in eastern, central, western and north-eastern area (see Fig. 2). Each control area has one observation well, and the four observation wells were studied and analyzed.

Saitama prefecture is part of Northern Kanto basin. The geology of the basin is classified into the alluvial and dilluvial deposits of the Quaternary period, Tertiary deposits and basement of the Miocene (Sato, 1995). Sedimentary rock in this area is composed of surface loam, clay, silt, sand and gravel. The aquifers from which water is abstracted mostly contain sand and gravel.

The main problem in the past related to groundwater abstraction was land subsidence. Land subsidence remains an important environmental issue, particularly in the extensive plain region in Japan such as Saitama, the Northern Kanto Plain. Land subsidence has induced indirect or compound damage (Murakami et al. 2002). In the 1950s, the land subsidence in the Kanto Plain was most severe in the southern part of Saitama prefecture, and gradually spread over areas such as the northern part of Saitama prefecture (Tanaka 2004).

In order to control and stop land subsidence and prevent the lowland from disaster, the national government has restricted groundwater withdrawal for industrial use since 1961 by the Industrial Water Law, and for air-conditioning use since 1963 by the Law Controlling Pumping of Groundwater for use in Buildings (Endo 1992). The guidelines for preventative measures for land subsidence in the northern Kanto basin were formulated in 1991, and Saitama prefecture local government has developed the GL monitoring system (Sato, 2000).

After implementing the regulations, the GL in Saitama prefecture was mostly stable. Figure 3 shows the relationship between monthly groundwater pumping, GL and land subsidence over 18 years (1986–2003) at Urawa (Saitama City). The pattern of land subsidence was similar to GL, and the GL pattern followed the pumping rate. In other words, we can say that land subsidence is very much influence by groundwater pumping. A spike of subsidence or GL is due to the overpumping period.

RESULTS AND DISCUSSION

Correlation Among Observed Wells

One of the most important steps in the development of any prediction model is the selection of appropriate input variables. When the relationship to be modeled is not well understood, an analytical technique, such as cross-correlation, is often employed. The analysis of monthly GL of candidate inputs and desired output was

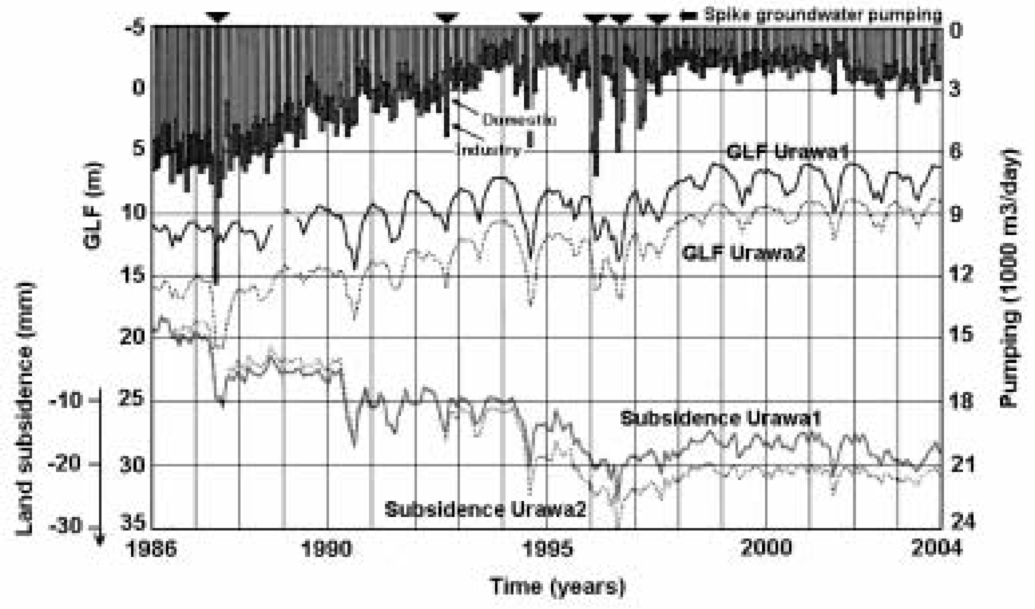

Fig. 3 Trend of GL and land subsidence due to the groundwater pumping in Saitama city (adopted from Annual report of land subsidence in Saitama prefecture, 2003)

performed by investigating the relationship between them using cross-correlation. This study was in the plain area with a case study of four observation wells representing the control area. The five surrounding wells with the best correlation coefficient, *r*, with respect to well studied were chosen as input for the ANN and GA model (see Table 1). The inputs have high correlation to the desired output. The depths of the inputs are almost in the same regime to the output desired (see Table 2).

ANN and GA Analysis

It is important to determine the appropriate network architecture in order to obtain satisfactory results. After a number of trial and error methods performed for backpropagation algorithms, 3 hidden nodes with 5 input nodes and 1 output node were considered, and the maximum epoch was 5000. The activation function used is the logistic sigmoid function. Normally, the data set for ANN needs to be divided into three parts. The first part is for the training, the second part for validation and the third part for testing. However, the length of data is not big enough, so only two parts are considered in this study, namely training and testing. The only difference between testing and validation is that if the error of the validation increases, the training is stopped. In this study these two terms were used synonymously. The length of training set was 60 samples over five years (from 1997 to 2001), and the testing set was 36 samples over three years (from 2002 to 2004).

Table 3 provides the performance of prediction results for the training and testing period in terms of the determination coefficient (R-squared) and root means squared error (RMSE), respectively. During the training period, the results mostly indicate that ANN is a potential technique for GL prediction. However, the performances were not so good for some prediction in testing period. It was found that Model 2 and Model 3 mostly gave better results during the testing period, except for Tokorozawa2. It can be inferred that a time lag of (t-1) and (t-2) of wells concerned was a significant contribution to the ANN calculation model. The Urawa2 that has a high GL fluctuation and the depth2 of the inputs are in the same range or regime that why it can give an excellent prediction result in the testing period. For the observation wells Koshigaya Hgs1, Tokorozawa2 and Washimiya2, the testing period contain the values out of the range used for the training period. In this case, ANN usually cannot generate a good result for prediction in the testing period. ANN performance is constrained by the quantity (and quality) of data available (Coppola et al., 2003). The poor prediction can be resulted when the testing data contain values outside the range of those used for training (Maier and Dandy, 2000). ANNs are unable to extrapolate beyond the range of data used for training (Flood and Kartam, 1994; Minns and Hall, 1996; Maier and Dandy, 2000).

Figure 4 provides a scatter plot of the prediction deviation from the observed GL during the testing period using input Model 2. The deviation is denoted as a difference between calculated and observed GL. Positive

Table 1 The correlation coefficient between inputs and desired output

Input	The correlation coefficient (r)							
	Koshigaya Hgs1		Urawa2 (U2)		Tokorozawa2(T2)		Washimiya2 (W2)	
X1	Kasukabe Ch2	0.969	Urawa1	0.954	Tokorozawa1	0.961	Kuki	0.958
X2	Yashio1	0.965	Kawagoe	0.899	Kasukabe Ch3	0.942	Satte1	0.945
X3	Yashio2	0.958	Urawa Hgs	0.888	Koshigaya Hgs1	0.935	Gyoda1	0.917
X4	Kasukabe Ch3	0.955	Toda2	0.871	Kasukabe Ch2	0.930	Koshigaya Hgs3	0.871
X5	Tokorozawa1	0.954	Kawashima2	0.837	Iwatsuki	0.926	Kurihashi	0.912

Table 2 The well depth of inputs with the correlation coefficient presented in Table 1

Input	The well depth (meters)							
	Koshigaya Hgs 1(315)		Urawa2 (250)		Tokorowaza2 (240)		Washimiya1 (415)	
X1	Kasukabe Ch2	315	Urawa1	150	Tokorozawa1	415	Kasukabe Ch1	600
X2	Yashio1	300	Kawagoe	200	Kasukabe Ch3	215	Kawashima1	300
X3	Yashio2	150	Urawa-E	228	Koshigaya Hgs1	315	Koshigaya	600
X4	Kasukabe Ch3	215	Toda2	142	Kasukabe Ch2	315	Tokorozawa1	415
X5	Tokorozawa1	415	Kawashima2	190	Iwatsuki	250	Koshigaya Hgs1	315

Urawa2(250) : Urawa1 observation well with depth of 250 meters.

Table 3 Performance of ANN model using for five years training and three years testing period

No.	Wells	Model 1		Model 2		Model 3	
		Training	Testing	Training	Testing	Training	Testing
				R-squared			
1.	Koshigaya Hgs1	0.9810	0.5990	0.9815	0.8470	0.9831	0.8427
2.	Urawa2	0.9888	0.9036	0.9922	0.9341	0.9793	0.9708
3.	Tokorozawa2	0.9960	0.7816	0.9555	0.6399	0.9533	0.5807
4.	Washimiya2	0.9472	0.4185	0.9035	0.6516	0.9309	0.6582
				RMSE			
1.	Koshigaya Hgs1	0.1572	0.2465	0.1555	0.3285	0.2115	0.3104
2.	Urawa2	0.1279	0.3007	0.1294	0.2643	0.1923	0.1681
3.	Tokorozawa2	0.2993	0.7734	0.5583	0.8288	0.4835	0.6788
4.	Washimiya2	0.3778	0.2955	0.3618	0.2591	0.3157	0.2469

Model 1: using inputs best 5 having best relation to desired output
Model 2: using inputs best 4 plus one step time lag (t-1) of well studied
Model 3: using inputs best 3 plus one step time lag (t-1) and (t-2) of well studied

deviation values indicate that the calculation overpredicts GL, whereas negative deviation values are under predicted. Overprediction denotes that the calculated is a more positive depth than observed, and underprediction means that an observation peizometric head is more positive than predicted. In generally, the outputs model were overpredicted. The deviations are mostly less than ± 1 meter, except for Washimiya 2, which lay on 1.5 meters. It can be said that the calculations model was acceptable for predicting the GL fluctuation.

Table 4 shows the performance of monthly GL prediction in terms of R-seq and RMSE, respectively. GA calculation used 100 population, five-string input, 60 samples (five years) for the training period, and 36 samples (three years) for the testing period, same as ANN analysis. The three input Models were also applied to the LC-GA approach. In general, LC-GA gave a satisfying prediction result for the training and testing period. Model 2, that had input of the best four in correlation and one time lag $x(t$-1) of the wells studied, had slightly better results than the other models in

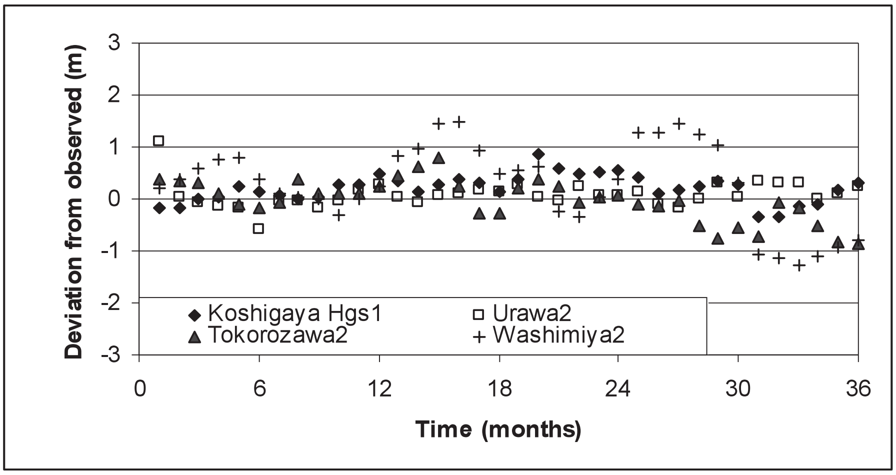

Fig. 4 Prediction deviation from observed GL during testing period using input Model 2

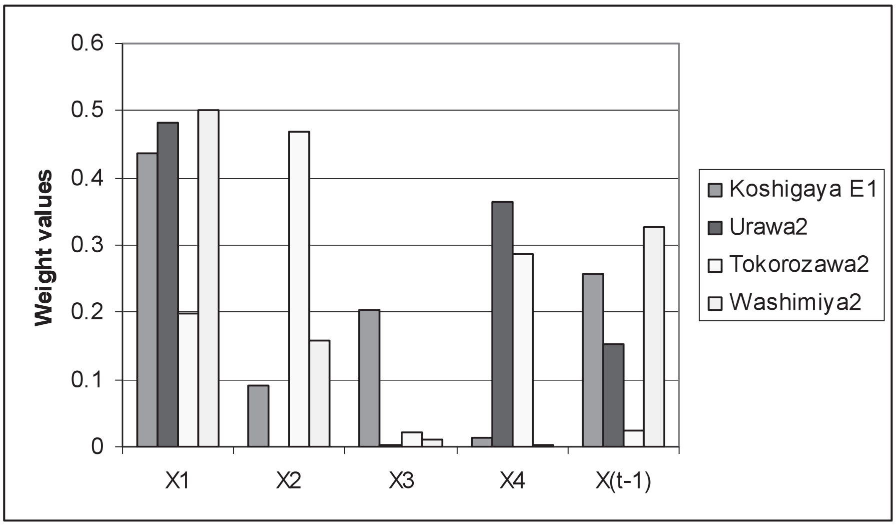

Fig. 5 The weight parameter (α) of the four observation wells for Model 2

Table 4 Performance of LC-GA model using for five years training and three years testing period

No.	Wells	Model 1		Model 2		Model 3	
		Training	Testing	Training	Testing	Training	Testing
				R-squared			
1.	Koshigaya Hgs1	0.9714	0.7502	0.9773	0.7837	0.9772	0.7830
2.	Urawa2	0.9813	0.8851	0.9847	0.9320	0.9624	0.9654
3.	Tokorozawa2	0.9471	0.6896	0.9441	0.7037	0.9403	0.6729
4.	Washimiya2	0.8617	0.7703	0.8794	0.8649	0.8796	0.8638
				RMSE			
1.	Koshigaya Hgs1	0.2057	0.1980	0.1919	0.1927	0.1919	0.1929
2.	Urawa2	0.2150	0.4124	0.1927	0.3379	0.2553	0.3182
3.	Tokorozawa2	0.2433	0.3792	0.2571	0.3789	0.2595	0.3838
4.	Washimiya2	0.5278	0.4047	0.4817	0.3976	0.4817	0.3991

training and testing period. It means that the time lag (t-1) gave a significant contribution to the calculation. The values of weight or coefficients (α) of each input of the four observation wells using Model 2 are shown in Fig. 5. The general tendency shows that the input with the highest correlation to the target has biggest weight values.

For all Models used, the RMSE were about 0.5m in the training and testing periods. If we compare the RMSE values, the LC-GA model and ANN model

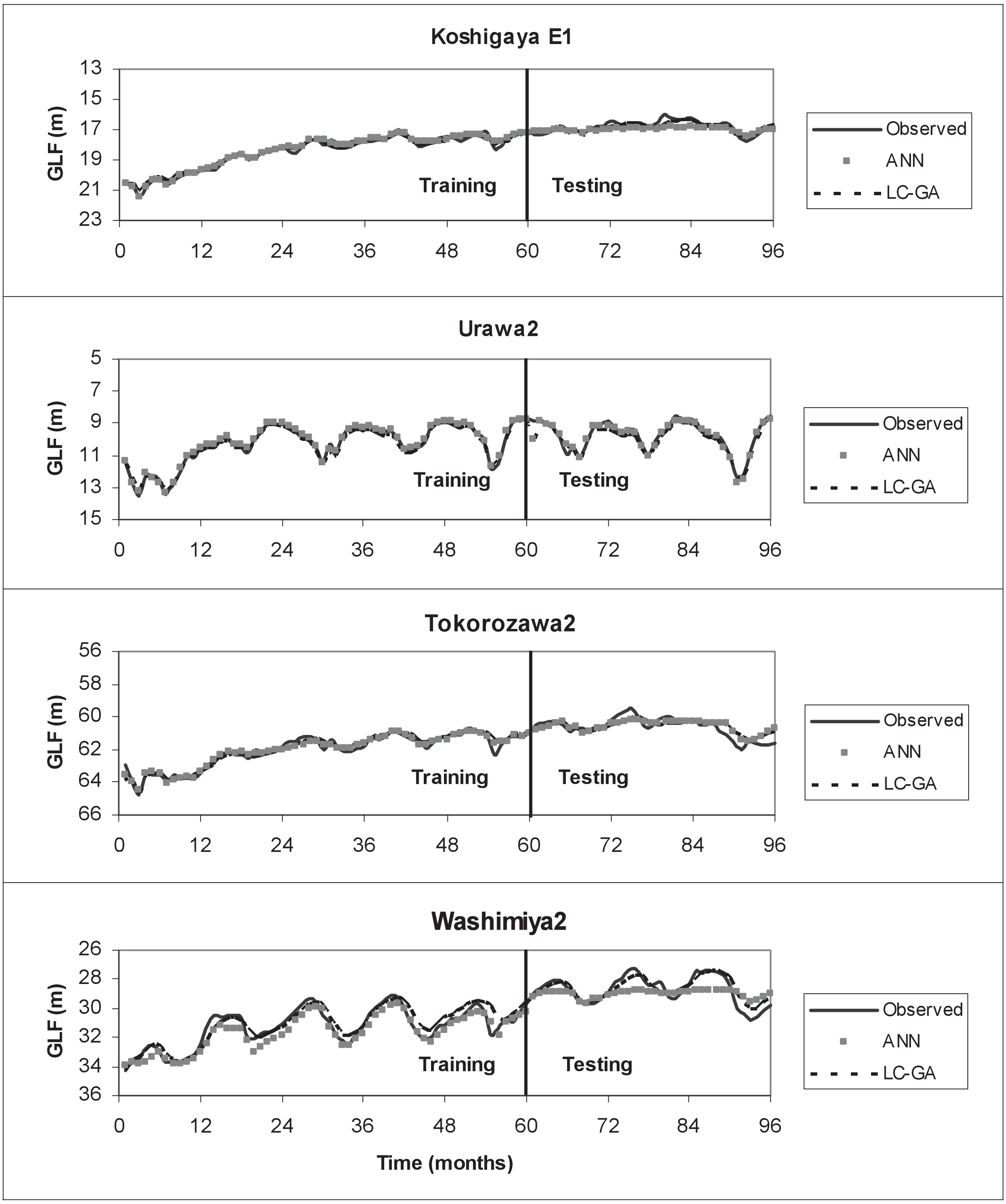

Fig. 6 Comparison of prediction results to observed values of ANN and LC-GA models for training and testing period using input Model

have not so big different performance results except for Tokorozawa2, the LC-GA is better than ANN model. Figure 6 shows the comparison results of prediction to observed values for training and testing period using input Model 2 for LC-GA and ANN methods. It is clear that LC-GA still can approach the pattern of fluctuation in testing period even though the testing samples are out side the of training data.

CONCLUSION

In this paper, a stochastic model as a potential method for analyzing GL has been investigated by using an ANN and LC-GA model. The monthly GL fluctuation from four observation wells in a plain area of Saitama prefecture was analyzed. The forecasting results of the ANN and LC-GA model were studied for monthly GL fluctuation. In general, the prediction from ANN and GA indicate that they can provide satisfactory predictions even for short monthly GL data observation. The performance evaluation criteria, the determination coefficient (R-squared) and the RMSE can be used as indicators of accuracy for the model evaluated.

The input Model 2 had better results than others. Prediction results suggest that input Model 2 can be a good arrangement of the data input for analyzing GL fluctuation using ANN and LC-GA. It indicated that a one time lag included in the data input made significant contributions to the model. From calculating the results, the LC-GC was in general slightly better than the ANN model. This result gives significant information for local governments to conduct GL monitoring. To build a monitoring system using the ANN or LC-GA model, other input parameters such as rainfall, stream discharge and pumping rate should be considered to derive results that are more precise.

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REFERENCES

ASCE Task Committee R.S. (2000a). Artificial neural networks in hydrology. I: Preliminary concepts. Journal of Hydrologic Engineering, 5:115–123.

ASCE Task Committee R.S. (2000b). Artificial neural networks in hydrology. II: Hydrologic application. Journal of Hydrologic Engineering, 5:123-137.

Balkhair, K.S. (2002). Aquifer parameters determination for large diameter wells using neural network approach. Journal of Hydrology, 265:118–128.

Coppola, Jr. E., Poulton, M., Charles, E., Dustman, J. and Szidarovszky, F. (2003). Application of artificial neural networks to complex groundwater management problems. Natural Resources Research, 12:303-320.

Coulibaly, P., Anctil, F., Aravena, R. and Bobée, B. (2001). Artificial neural network modeling of water table depth fluctuations. Water Resources Research, 37:885-896.

Daliakopoulos, L.N., Coulibaly, P., Tsanis, I.K. (2005). Groundwater level forecasting using artificial neural networks. Journal of Hydrology, 309:229-240.

Endo, T. (1992). Confined groundwater system in Tokyo. Environmental Geology, 20: 21-34.

Flood, I. and Kartam, N. (1994). Neural networks in civil engineering. I: Principles and understanding. Journal of computing in Civil Engineering , 8:131-148.

Gen, M. and Cheng, R. (1997). Genetic algorithms and engineering design. John Wiley & Sons, Inc. New York.

Giacobbo, F., Marseguerra, M. and Zio, E. (2002). Solving the inverse problem of parameter estimation by genetic algorithms: the case of groundwater contaminant transport model. Annals of Nuclear Energy, 29:967–981.

Goldberg, D. (1989). Genetic algorithms search, optimization and machine learning, Addison-Wesley, Reading, MA.

Katsifarakis, K.L., Karpouzoz, D.K. and Theodossiou, N. (1999). Combined use of BEM and genetic algorithms in groundwater flow and mass transport problems. Engineering Analysis with Boundary Elements, 23:555-565.

Lallahem, S., Mania, J., Hani, A. & Najjar, Y. (2005). On the use of neural networks to evaluate groundwater levels in fractured media. Journal of Hydrology, 307:92-111.

Lee S., Ryu, J.H., Won, J.S. and Park, H.J. (2004). Determination and application of the weights for landslide susceptibility mapping using an artificial neural network. Engineering Geology, 71:289-302.

Maier, H.R. & Dandy, G.C. (2000). Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Environmental Modelling and Software,15:101-124.

Minns, A.W., Hall, M.J. (1996). Artificial neural networks as rainfall-runoff models. Hydrological sciences Journal, 41:399-417.

Morshed, J. and Kaluarchchi, J.J. (1998). Application of artificial neural network and genetic algorithm in flow and transport simulations. Advances in Water Resources, 22:145 – 158.

Murakami, S., Yasuhara, K. and Mochizuki, N. (2002). An observational prediction of land subsidence for a GIS-AIDED monitoring system of groundwater level. Lowland Technology International, 4:46-61.

Nayak, P.C., Rao, Y.R.S. and Sudheer, K.P. (2006). Groundwater level forecasting in a shallow aquifer using artificial neural network approach. Water Resources Management, 20:77-90.

Prasad, K.L. and Rastogi, A.K. (2001). Estimating net aquifer recharge and zonal hydraulic conduntivity values for Mahi right bank canal project area, India by genetic algorithm. Journal of Hydrology, 243:149–16.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J. (1986). Learning representations by back-propagation error. Nature, 323:533-536.

Ranjithan, S., Eheart, J.W. and Garrett, J.H. (1993). A neural network-based screening for groundwater reclamation under uncertainty. Water Resources Research, 29:563-574.

Sato, K. (1995). Comprehensive measure for land subsidence in Japan, a case study. Annual report of Geosphere Research Institute Saitama University (Japan), 20:17–22.

Sato, K. (2000) A new control system of groundwater resource. Proc. Int. Symposium on Groundwater (groundwater Updates). Springer Verlag: 13-16.

Tanaka, T. (2004). Groundwater resources, development and management in the Kanto Plain, Japan. Satellite Symposium. available at
http://www.nourin.tsukuba.ac.jp/~tasae/2004/2004Satellite%20Symposium.htm